



Estimation of Rigidity of Concrete Based on Multi Parameters Using Artificial Bee Colony Optimization Method with Levy Flight Distribution

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Abstract. The rigidity of the materials used in the structures affects most deformation characteristics. Therefore, obtaining information about the rigidity of materials is essential for the behavior of the structures. In the study, 32 different equations were derived by usage of eight parameters in various combinations to estimate elastic modulus of concrete. These parameters are compressive strength, unit weight, water-cement ratio, consistency, cement amount, fine aggregate – coarse aggregate ratio and air content. Multidimensional nonlinear regression models were generated between equation models and test results. The optimization process is applied to solve regression models. An improved version of Artificial Bee Colony Optimization algorithm by adding levy flight distribution (ABC_LF) is used as the optimization method. Estimated values are compared to test results to determine the goodness of the equations. The effectiveness of the parameters is investigated according to the comparison as well.

1. Introduction

Elastic Modulus is one of the essential mechanical property of concrete to predict its behavior. In some cases, the elastic modulus of concrete can change with different mixture even if the same compressive strength of concrete is provided [1–3]. Stress-Strain curve is an exact way to obtain the elastic modulus. However, experimental tests are required to get a stress-strain curve that causes time and money loss. Usage of the general equation presents a fast and economical solution to estimate the elastic modulus of concrete. Different formulas are proposed by many researchers to compute the modulus of elasticity [4]. Most of them based on the compressive strength are not suitable for both normal and high strength. Many models suggested in the literature could not precisely predict the modulus of elasticity made with different compositions.

In the literature, there are few studies available which contain a mathematical model for prediction of the elastic modulus of concrete [5]. In 2005, Demir proposed a fuzzy-logic model to predict elastic modulus [6].

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Demir also predicted elastic modulus of standard and high strength concrete by artificial neural networks in 2008 [7]. Gandomi et al. formulate elastic modulus of concrete using linear genetic programming [8]. N. Ahmadi-Nedushan predicted elastic modulus of standard and high strength concrete using adaptive-network-based fuzzy inference system (ANFIS) and optimal nonlinear regression models [9]. Yan and Shi predicted elastic modulus of standard and high strength concrete by support vector machine [10]. Aydın et al. predicted concrete elastic modulus using an adaptive neuro-fuzzy inference system [11]. Topçu and Sarıdemir predicted elastic modulus of waste AAC aggregate concrete using artificial neural network [12]. In general, the prediction models obtained from these studies depend on few parameters such as the strength of concrete. Hence, multi-parameter elastic modulus estimation model was not encountered in the literature.

Nonlinear regression models should be preferred to generate good estimation model. The solution of nonlinear regression models standard is not an easy task for researchers. Using a large number of parameters in the models makes it more difficult to get the solution. Standard mathematical methods are not adequate to solve these models. Meta-heuristic optimization techniques are useful tools for these problems. ABC method is one of the well-known meta-heuristic optimization method developed by Karaboga and Basturk [13–15]. Researchers used the ABC method in many engineering fields such as electric power systems [16], air vehicle path planning [17], the design of civil engineering structures [18–25]. The ABC method is also used to solve regression models such as symbolic regression [26], support vector regression system [27, 28], stepwise regression – correlation [29]. The ABC method showed efficient performance in these studies. In the survey, multi parameters have been used for regression models. This case increases the dimension of the optimization problem. Divergence might be encountered when the classical version of the ABC algorithm is used for large scale optimization problems. Some researchers [19, 20, 30] have used Levy Flight distribution to improve the ABC algorithm's performance and have achieved satisfactory results in their studies. Therefore, the improved version of the ABC method called ABC.LF is preferred in the study.

As a result of the literature study, it is seen that the study has novelties in terms of testing the performance of the ABC method in multi-dimensional regression problems and investigating experimental parameters to predict concrete elastic modulus.

2. Mathematical Modeling

2.1. Nonlinear regression model

In the study, the equation models have been investigated to determine the modulus of elasticity of concrete with respect compressive strength, unit weight, water-cement ratio, consistency, cement amount, fine aggregate – course aggregate ratio and air content. The general formula of the equation models is described as follows;

$$E^*(\sigma_B, \gamma, w/c, Sl, C, A, AC) = x_1 \cdot \sigma_B^{x_2} \cdot \gamma^{x_3} \cdot w/c^{x_4} \cdot Sl^{x_5} \cdot C^{x_6} \cdot A^{x_7} \cdot AC^{x_8} \quad (1)$$

where, σ_B is compressive strength, γ is unit weight, (w/c) is water–cement ratio, Sl is consistency, C is cement amount, A is fine aggregate–course aggregate ratio, AC is air content and $\vec{x} = [x_1, x_2, \dots, x_8]$ are the factors of the equations. Usage of some parameters together may have negative effects on the model estimation. Therefore, thirty-two different equations are derived with respect to combinations of the parameters.

2.2. Optimization problem

To the solve nonlinear regression model, the optimization tool has been used. The optimization process consists of two main phases. These are modeling and analyses stages. In the modeling phase, the design problem is converted to the optimization problem. The appropriate optimization method is selected and applied to the optimization problem in the analyses phase.

Two primary parameters called objective function, and the design variable vector should be defined to generate the optimization problem. The objective of the optimization problem is defined as minimizing the

error (the difference between the test data and the estimated data obtained from the equation model). Root Mean Square Error (RMSE) function of mean square error is used as an error function which is described as follows;

$$RMSE(\vec{x}) = \sqrt{\frac{\sum_{i=1}^N (E_i - E_i^*(\vec{x}))^2}{N}} \tag{2}$$

where N is the total number of test data, i is the subscript representing the data number, E is the value of the obtained from tests, E^* is the approximate value of the data obtained from the equation model. Design variable vector is a vector which contains parameters traded as a variable during the optimization process. Factor vector of the equation parameters (\vec{x}) is defined as design in the current optimization problem. Fitness (performance) of each equation model (F_i) is inversely proportional to its objective function value.

3. Optimization Method: Artificial Bee Colony Optimization Method with Levy Flight Distribution (ABC_LF)

3.1. Theory

The ABC method is one of the well-known meta-heuristic based optimization technique which emerged in 2005 [13]. The hypothesis of the ABC method is based on the community behavior of honey worker bees. In the ABC algorithm, the worker bees are categorized into three groups called employed, onlooker and scout bees. Employed bees collect nectars around determined food sources, record information about better food sources and share with the colony. Onlooker bees decide the most convenient food sources and fly to collect nectars. Scout bees detect the consumed food sources and find new food sources on behalf of the food sources.

A Levy flight is a random walk strategy developed by French mathematician Paul Levy. Step-lengths of the random walk are calculated using heavy-tailed probability distribution. In the literature, many simplified distribution functions represents the Levy Flight distribution function. In the study, Mantegna function [31] is utilized to calculate the step length and its simplified version are described as follows:

$$SL = \alpha \oplus levy(\beta) = 0.01 \frac{N(0, \sigma_u^2)}{N(0, \sigma_v^2)^{\frac{1}{\beta}}}; \sigma_u = \left[\frac{\Gamma(1 + \beta) \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \beta 2^{\frac{\beta-1}{2}}} \right]^{1/\beta}; \sigma_v = 1 \tag{3}$$

where, α is random step size constant, β is Levy flight parameter, $levy$ is the Levy flight distribution function, \oplus is entry wise multiplication, $N(m, \sigma)$ is random number function obtained from a normal distribution having m mean and σ standard deviation and, Γ is the gamma function ($\Gamma(z) = \int_0^\infty t^{z-1} \bullet e^{-z}$).

3.2. ABC_LF method for nonlinear regression analysis

In the study, the ABC method is utilized to find the optimum equation parameters described in section 2, concerning minimizing modeling error. The expressions of the ABC theory are explained for the current optimization problem in Table 1.

According to these expressions, the main steps of the ABC algorithm can be defined as follows;

Step1: Initial equation models are randomly generated as follows;

$$X_{i,j} = int(lb_j + (ub_j - lb_j) \bullet rnd(0, 1)); i = 1, 2, \dots, FS \quad j = 1, 2, \dots, n \tag{4}$$

Where; X is the solution pool which contains the factors of the all equation models in the algorithm memory, lb and ub respectively are the lower and the upper boundaries of the equation constants, FS is the

total number of food source defined in the algorithm, n is total number of factors in the equation, $rnd(0, 1)$ is a random number generated from interval the $[0-1]$ and int is a function which rounds the result with respect to predefined decimal. Then, the algorithm calculated the fitness values of the initial equation models according to Eq. 2 and assign an initial trial number of the models as zero.

Step 2: Employed phase is performed in this step. In this phase, current equation models are modified according to the following formula;

$$X_{i,j}^{new} = int \left(X_{i,j} + (X_{i,j} - X_{i,k}) \bullet rnd(-1, 1) \right); i \neq k \tag{5}$$

Where k is a subscript of the neighbor equation model which is chosen randomly from among current equation models in the algorithm memory, then, the fitness values of the equation models are calculated and compared with their previous versions. If the modified solutions have better fitness values, they substitute with their previous ones. Otherwise, the algorithm does not accept the replacements and holds the previous versions. This update process is named as “Greedy Selection.” If replacement is performed, the algorithm assigns the trial number of the modified equation model as zeros. Otherwise, the algorithm increases the trial numbers of the previous equation models by one.

Step 3: Onlooker bee phase is performed in this step. In the onlooker bee phase, the most appropriate food sources are detected according to the selection probabilities of the equation models. Selection probability (Pr) of each equation depends on its fitness value which is described as follow;

$$Pr = \frac{F(\vec{x})}{\sum_j^{NS} F(\vec{x})_j} \tag{6}$$

Then the detected food sources are modified, and greedy selection is applied in the same manner described in step 2

Step 4: The algorithm uses the scout bee phase in this step. Scout bees determine the consumed food source. In other words, equation models whose trial values exceed the food limit are detected. Then these models assigned to absorbed food sources are subtracted from the algorithm memory.

The classical version of the ABC algorithm adds new solutions using the random selection method as illustrated in Eq. 4. Candidate solutions randomly generated using a random selection method is unlikely to be better than the current solutions. Therefore divergence may occur in the algorithm. The algorithm uses Levy Flight distribution to overcome the problem in step 4. In the Levy Flight distribution, the candidate solution is generated according to the following formula:

$$X_{ic,j}^{new} = int \left(X_{ic,j} + SL \bullet (X_{ic,j} - X_{ib,j}) \right); j = 1, 2, \dots, n \tag{7}$$

where ib and ic respectively are subscripts of consumed food source and the best food source in the memory.

After step 4, the algorithm checks the stopping criterion which is defined as reaching the maximum generation number of the candidate equation models. If the stopping criterion is satisfied, the algorithm is terminated, and the best equation model in the memory is assigned as the optimum solution. Otherwise, the algorithm goes back to step 2.

3.3. Determination of search parameters of the ABC-LF method

The ABC method uses four search parameters called the total number of food source (FS), food source limit (L), Levy flight parameter (β), the maximum generation number (gen_{max}). These parameters should be defined at the beginning of the algorithm and do not change in the optimization process. Values of these parameters directly affect the performance of the ABC method. Therefore, it is very important to determine the most appropriate search parameter values. Generally, sensitivity analysis is used to determine search parameter values. However, some researchers perform sensitivity analysis and find the most appropriate search parameter values [17, 19]. Based on these studies, search parameters of the current studies are determined as: $FS = 10$, $gen_{max} = 500$, $L = 50$ and $\beta = 1.5$.

Table 1: Explanation of the ABC algorithm expressions

Expression	Explanation
Food source	Candidate equation model
Location of the food source	Values of the equation parameters in the model
nectars around determined food sources	Modifying the current equation model and calculating its performance
Deciding the most convenient food sources	Selection the equation model according to its fitness
Consuming the food source	Usage of the equation model in the algorithm memory

4. Results

In the study, twenty-seven experimental tests having different concrete mixtures have been performed are tested to find the equation models. The components and mechanical properties of the concretes obtained by the experiments are taken from the literature[32]. The constants of the equation models mentioned in section 2 are optimized using ABC_LF algorithm. The lower boundaries, the upper boundaries, and increments of the equation constants are shown in Table 2. Obtained the optimum equations constants and RMSE error values of equations are illustrated in Table 3. According to the table, the 25th equation model has the minimum RMSE error value which is described as follows;

$$E^*(\sigma_B, \gamma, w/c, SI) = 2570 \cdot \sigma_B^{0.407} \cdot \gamma^{0.161} \cdot (w/c)^{0.042} \cdot SI^{-0.098} \tag{8}$$

The estimated rigidity values of the best model are compared to real data in Figure 1. Performance of the equation models also tested in six different correlation and error functions called the determination coefficient (R^2), the adjusted determination coefficient (R^2_{adj}), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and normalized root mean square error (NRMSE).

The correlation and error values obtained from these functions are given in Table 4. According to the table, R^2 and R^2_{adj} values respectively vary from 0.91 and 0.83 to 0.98 and 0.96; the maximum MAPE value is 3.3%; the average value of the NRMSE is 0.06. Although values of the MAE seem to be high, these errors do not indicate that the models present good estimations due to the fact that actual data is quite big. In general, the predicted values were very close to the experimental data. Compared with the results of some methods in the literature, it shows the usability of the method utilised in practice.

5. Conclusion

In the study, novel, nonlinear and multidimensional equation models are derived using ABC_LF method. According to the results, ABC_LF algorithm showed efficient performance to find optimum equation models.

Thus, the rigidity of the materials which are determinative in the behavior of the structures that are important in engineering applications can be easily estimated even if they have different compositions. It is also an advantage that the method used provides different options. If desired, different relations established as output may be preferred for various purposes. In practice, the presence of too many variables normally limits predictability. However, this method has proved its potential to give accurate and precise outputs, although there are many variables. In addition, it is observed that σ_B , γ , w/c and SI parameters are more effective in model determination.

Table 2: lower and upper boundaries of equation factors

	ub	lb	incr
x_1	1000	6000	10
x_2	0	0.6	0.001
x_3	0	0.3	0.001
x_4	0	0.2	0.001
x_5	-0.5	0.1	0.001
x_6	0	0.5	0.001
x_7	0	0.5	0.001
x_8	-0.5	0	0.001

Table 3: the optimum equations constants and RMSE error values of equations

Eq. ID	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	RMSE
1	3930	0.362	0.087	N.A.	N.A.	N.A.	N.A.	N.A.	758.8
2	1630	0.409	0.179	N.A.	N.A.	N.A.	N.A.	-0.001	952.0
3	1320	0.353	0.232	N.A.	N.A.	N.A.	0	N.A.	765.1
4	3590	0.342	0.108	N.A.	N.A.	N.A.	0	-0.001	781.0
5	3590	0.364	0.075	N.A.	N.A.	0.03	N.A.	N.A.	787.4
6	4420	0.349	0.056	N.A.	N.A.	0.029	N.A.	-0.001	779.2
7	1000	0.33	0.278	N.A.	N.A.	0	0	N.A.	777.2
8	3430	0.37	0.093	N.A.	N.A.	0	0.079	-0.001	837.8
9	2490	0.344	0.192	N.A.	-0.105	N.A.	N.A.	N.A.	682.2
10	1360	0.41	0.265	N.A.	-0.174	N.A.	N.A.	-0.001	706.2
11	1960	0.443	0.175	N.A.	-0.11	N.A.	0.044	N.A.	836.2
12	5840	0.337	0.08	N.A.	-0.106	N.A.	0.054	-0.001	902.5
13	1000	0.391	0.299	N.A.	-0.162	0.013	N.A.	N.A.	675.3
14	4280	0.288	0	N.A.	-0.21	0.246	N.A.	-0.002	1041.2
15	5760	0.362	0.087	N.A.	-0.205	0.03	0.019	N.A.	872.7
16	4390	0.437	0.049	N.A.	-0.243	0.064	0.288	-0.001	1083.6
17	2100	0.401	0.157	0.065	N.A.	N.A.	N.A.	N.A.	728.9
18	3290	0.411	0.093	0.055	N.A.	N.A.	N.A.	-0.001	745.7
19	3500	0.448	0.076	0.125	N.A.	N.A.	0	N.A.	740.2
20	1580	0.441	0.18	0.109	N.A.	N.A.	0	-0.001	745.6
21	2330	0.382	0.15	0.044	N.A.	0	N.A.	N.A.	733.7
22	2300	0.323	0.172	0	N.A.	0.003	N.A.	-0.001	818.4
23	1320	0.416	0.101	0.165	N.A.	0.158	0	N.A.	789.6
24	1000	0.369	0.269	0.057	N.A.	0	0	-0.016	831.1
25	1090	0.441	0.273	0.094	-0.129	N.A.	N.A.	N.A.	540.8
26	2130	0.456	0.195	0.09	-0.172	N.A.	N.A.	-0.001	589.4
27	2180	0.495	0.16	0.094	-0.138	N.A.	0.023	N.A.	645.0
28	5290	0.557	0.024	0.2	-0.128	N.A.	0.033	-0.001	643.1
29	3420	0.421	0.079	0.075	-0.113	0.063	N.A.	N.A.	560.3
30	1600	0.35	0.133	0.081	-0.096	0.157	N.A.	-0.001	682.8
31	4070	0.472	0.056	0.112	-0.152	0.057	0	N.A.	561.9
32	1390	0.493	0.036	0.2	-0.182	0.267	0.1	-0.001	715.3

Table 4: The correlation and error values of the function estimations

Eq.	R^2	R^2_{adj}	MAE	MAPE	NRMSE	Eq.	R^2	R^2_{adj}	MAE	MAPE	NRMSE
1	0.9568	0.9135	577	2.200	0.06127	17	0.9604	0.9208	582	2.238	0.05861
2	0.9319	0.8638	797	2.861	0.07688	18	0.9583	0.9166	6049	2.289	0.06017
3	0.9561	0.9121	601	2.274	0.06175	19	0.9590	0.9180	605	2.358	0.05964
4	0.9543	0.9085	613	2.377	0.06302	20	0.9583	0.9166	633	2.406	.06015
5	0.9535	0.9069	616	2.303	0.06355	21	0.9597	0.9193	562	2.172	0.05918
6	0.9544	0.9088	591	2.271	0.06290	22	0.9497	0.8993	643	2.519	0.06610
7	0.9547	0.9093	609	2.359	0.06273	23	0.9550	0.9100	617	2.419	0.06251
8	0.9474	0.8948	654	2.520	0.06755	24	0.9485	0.8969	675	2.618	0.06688
9	0.9651	0.9303	541	2.077	0.05502	25	0.9780	0.9561	455	1.724	0.04366
10	0.9625	0.9251	578	2.143	0.05702	26	0.9739	0.9478	493	1.886	0.04760
11	0.9480	0.8961	644	2.269	0.06716	27	0.9687	0.9375	555	1.991	0.05209
12	0.9389	0.8777	784	2.972	0.07285	28	0.9690	0.9381	462	1.705	0.05184
13	0.9663	0.9327	553	2.068	0.05405	29	0.9776	0.9551	446	1.687	0.04414
14	0.9206	0.8412	845	3.255	0.08300	30	0.9650	0.9301	533	2.076	0.05508
15	0.9428	0.8857	675	2.600	0.07044	31	0.9767	0.9535	480	1.799	0.04493
16	0.9127	0.8254	856	3.304	0.08704	32	0.9616	0.9231	595	2.236	0.05776

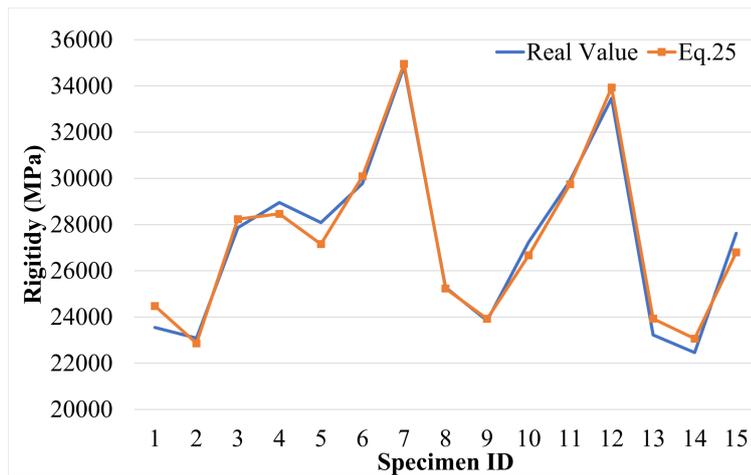


Figure 1: Comparison of real and the best-estimated values of rigidity.

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